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The Evolution of Education: A Macroeconomic Analysis

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─────────── ABSTRACT ───────────

Between 1940 and 2000 there has been a substantial increase of educational attainment in the United States. What caused this trend? We develop a model of schooling decisions in order to assess the quantitative contribution of technological progress in explaining the evolution of education. We use earnings across educational groups and growth in gross domestic product per worker to restrict technological progress. These restrictions imply substantial skill-biased technical change (SBTC). We find that changes in relative earnings through SBTC can explain the bulk of the increase in educational attainment. In particular, a calibrated version of the model generates an increase in average years of schooling of 48 percent compared to 27 percent in the data. This strong effect of changes in relative earnings on educational attainment is robust to relevant variations in the model and is consistent with empirical estimates of the long-run income elasticity of schooling. We also find that the substantial increase in life expectancy observed during the period contributes little to the change in educational attainment in the model.

Keywords: educational attainment, schooling, skill-biased technical progress, human capital.
JEL codes: E1, O3, O4.

1 Introduction

One remarkable feature of the twentieth century in the United States is the substantial increase in educational attainment of the population. Figure 1 illustrates this point. In 1940, about 8 percent of white males aged 25 to 29 had completed a college education, 31 percent had a high school degree but did not finish college, and 61 percent did not even complete high school.[1] The picture is remarkably different in 2000 when 28 percent completed college, 58 percent completed high school, and 13 percent did not complete high school. Although our focus is on white males, Figure 2 shows that the trends of Figure 1 are broadly shared across genders and races. The question we address in this paper is: What caused this substantial and systematic rise in educational attainment in the United States? Understanding the evolution of educational attainment is relevant given the importance of human capital on the growth experience of the United States as well as nearly all other developed and developing countries.

We develop a model of human capital accumulation to assess the quantitative importance of observed changes in relative earnings across educational groups in generating trends in educational attainment. Our finding is that changes in relative earnings can explain the bulk of the increase in educational attainment in the United States between 1940 and 2000. Our focus on relative earnings is motivated by data. Using the IPUMS samples for the 1940 to 2000 U.S. Census, we compute weekly earnings across three educational groups for white males of a given age cohort: less than high school, high school, and college.[2] Relative earnings among educational groups exhibit noticeable changes since 1940 as documented in Figure 3. For instance, earnings of college relative to high school increased by 22 percent (from 1.58 in 1940 to 1.94 in 2000), while the relative earnings of high school to less than high school increased by 30 percent (from 1.47 in 1940 to 1.92 in 2000).[3]

We argue that a change in relative earnings of 20 to 30 percent can generate a substantial increase in educational attainment. To illustrate this point, consider an elasticity of college attainment with respect to relative lifetime income of 8 as suggested by some empirical micro evidence. Then, a 20 percent increase in the earnings of college relative to high school can

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[1]In what follows we refer to the detailed educational categories simply as less than high school, high school, and college. See the appendix for details of data sources and definitions.

[2]Weekly earnings refers to pre-tax wage and salary income divided by the number of weeks worked. In what follows, we refer to weekly earnings, earnings, and income interchangeably.

[3]Figure 3 illustrates patterns that have been emphasized in the wage-structure literature. Both the returns to college and high school exhibit increasing trends. The return to college decreased during the 1940s and 1970s and rose sharply during the 1980s and 1990s. Acemoglu (2002), for example, reports a similar pattern for the returns to college. The compression observed in the 1940s was documented and discussed by Goldin and Margo (1992).

increase college attainment by a factor of 4.3, which compares to 3.7 in the data. This calculation suggests that observed changes in relative earnings are quantitatively important in explaining the rise in educational attainment between 1940 and 2000. However, relative earnings and the implied elasticity of educational attainment are endogenous to education decisions. As a result, a quantitative model is needed in order to discipline and disentangle the relevant forces and to provide a quantitative assessment. The model would also need to be able to capture the changes in returns to schooling across educational categories.

We consider a model of human capital accumulation that features discrete schooling choices, heterogeneity in schooling utility, a standard human capital production function that requires the inputs of time and goods as in Ben-Porath (1967), and exogenous driving forces that take the form of neutral and skill-biased productivity parameters in the production function. Discrete schooling choice is relevant because the distribution of people across years of schooling in the data is concentrated around completion years. Also, the discrete choice allows the model to match distribution statistics such as those presented in Figure 1 as opposed to just averages for a representative agent. The assumption that agents are heterogeneous in the marginal utility from schooling time is common in both the macro literature (e.g. Bils and Klenow (2000)) as well as the empirical labor literature (e.g., Heckman, Lochner, and Taber (1998)).[4] Moreover, given the discreteness of schooling levels, the model with heterogeneity implies that changes in exogenous factors have smooth effects on aggregate variables such as educational attainment and income.

We implement a quantitative experiment to assess the importance of changes in relative earnings on the rise of educational attainment. We discipline the exogenous variables in the model, i.e., the pace of technical change, by using data on relative earnings among workers of different schooling groups. More generally, the parameters of the model are chosen to match a set of key statistics, including educational attainment in 2000, earnings differentials across schooling levels from 1940 to 2000, and the average growth rate of gross domestic product (GDP) per worker between 1940 and 2000. This quantitative strategy follows the approach advocated by Kydland and Prescott (1996). In particular, we emphasize that the parameter values are not chosen to fit the data on educational attainment from 1940 to 2000, instead they are chosen to mimic the trends in relative earnings. The answer to the quantitative importance of changes in relative earnings over time is measured by the capacity of the model to generate substantial trends in educational attainment as observed in the data.

The main findings are as follows. Results from the baseline model show that changes

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[4]An additional source of heterogeneity may be through "learning ability." Navarro (2007) finds, however, that individual heterogeneity affects college attendance mostly through the preference channel.

in relative earnings across schooling groups generate a substantial increase in educational attainment that is consistent with the trends in each educational category. As a summary statistic, the model generates a 48 percent increase in average years of schooling between 1940 and 2000 compared to the 27 percent increase in the U.S. data. The bulk of this increase in the model is generated by the change in high-school to less-than-high-school relative earnings and relatively less by the change in college to high-school relative earnings. The quantitative contribution of relative earnings to educational attainment depends on the assumption about their change after the year 2000. Assuming no further change in relative earnings after 2000, the model is closer to replicating the change in educational attainment in the time series data – a 39 percent increase in educational attainment versus 48 in the baseline calibration. We show that these results are robust to relevant variations in the model. First, although life expectancy has increased substantially during the period of analysis, we find that this change generates a small increase in educational attainment in the model. Returns to human capital are higher early in the life cycle rather than later so changes in life expectancy accrue low returns for schooling investment. Second, we extend the model to allow for on-the-job human capital accumulation and find little difference with our baseline results. This is due to the systematic fall in the returns to experience for recent cohorts in the United States – see for instance Manovskii and Kambourov (2005). Third, the increase in educational attainment is the same as in the baseline model when we extend it to allow for TFP-level effects. In this case, changes in relative earnings generate about 90 percent of the increase in educational attainment in the model as opposed to 100 percent in the baseline.

Our model builds on the human capital literature, most notably Becker (1975), Ben-Porath (1967), Mincer (1974), and Heckman (1975). It is also close to Heckman, Lochner, and Taber (1998). However, Heckman, Lochner, and Taber (1998) focus on explaining the increase in U.S. wage inequality in the recent past (see also Topel (1997)). Our emphasis is on understanding the rise in educational attainment conditional on matching changes in the returns to schooling. Our work is close to a literature in macroeconomics assessing the role of technical progress on a variety of trends such as women's labor supply (e.g., Greenwood, Seshadri, and Yorukoglu (2005)), fertility and the baby boom (e.g., Greenwood, Seshadri, and Vandenbroucke (2005)), the structural transformation across countries and regions (e.g., Gollin, Parente, and Rogerson (2002) and Caselli and Coleman (2001)), the transition from stagnation to modern economic growth (e.g., Hansen and Prescott (2002)), among others.[5] Our paper is also related to the labor literature emphasizing the connection between technology and education – for instance Goldin and Katz (2007) – and the literature on wage inequality emphasizing skill-biased technical change – see for instance Juhn, Murphy,

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[5]See Greenwood and Seshadri (2005) for an excellent survey of this broad literature.

and Pierce (1993) and Katz and Author (1999). We recognize that technological progress may not be the only explanation for rising education – for instance Glomm and Ravikumar (2001) emphasize the rise in public-sector provision of education – and that educational attainment has been rising well before 1940. Our focus on the period between 1940 and 2000 follows from data restrictions and the emphasis in the labor literature on technological progress as the likely cause of rising wage inequality. In the broader historical context, other complementary explanations may be needed – see Kaboski (2004) on the decline of direct schooling costs.

The paper proceeds as follows. In the next section we describe the model. In Section 3 we conduct the main quantitative experiments. Section 4 extends the model to allow for changes in life expectancy, returns to experience, and TFP-level effects. In Section 5 we discuss our results by performing a series of sensitivity analysis and by placing the results in the context of the related literature. We conclude in Section 6.

2 Model

In this section we develop a model of schooling decisions in order to assess the quantitative contribution of technological progress to the rise of educational attainment in the United States.

2.1 Environment

The economy is populated by overlapping-generations of constant size normalized to one. Time is discrete and indexed by $t = 0, 1, \ldots, \infty$. Agents are alive for T periods and are ex-ante heterogeneous. Specifically, they are indexed by $a \in \mathbb{R}$, which represents the intensity of their (dis)taste for schooling time, and is distributed according to the time-invariant cumulative distribution function A. We assume that the utility cost is observed before any schooling and consumption decisions are made. We also assume that there is no uncertainty in the model.

An individual's human capital is denoted by $h(s, e)$ where s represents the number of periods spent in school and e represents expenses affecting the quality of schooling. Both s and e are choice variables. There are three levels of schooling labeled 1, 2 and 3. To complete level i an agent must spend $s_i \in \{s_1, s_2, s_3\}$ periods in school and, therefore, is not able to work before reaching age $s_i + 1$. The restriction $0 < s_1 < s_2 < s_3 < T$ is imposed so that level 1 is the model's counterpart to the less-than-high-school level discussed previously.

Similarly, level 2 corresponds to high-school and level 3 to college. Aggregate human capital results from the proper aggregation of individual's human capital across generations and educational attainment. It is the only input into the production of the consumption good. The wage rate per unit of human capital is denoted by $w(s)$ for an agent with s years of schooling. This is to allow for the possibility that technological progress affects the relative returns across schooling groups. Credit markets are perfect and r denotes the gross rate of interest.

2.2 Technology

At each date, there is one good produced with a constant-returns-to-scale technology. This technology is linear in the aggregate human capital input,

$$Y_t = z_t H_t,$$

where z_t is total factor productivity. The stock of aggregate human capital, H_t, is also linear

$$H_t = z_{1t} H_{1t} + z_{2t} H_{2t} + z_{3t} H_{3t}, \tag{1}$$

where H_{it} is the stock of human capital supplied by agents with schooling s_i, and z_{it} is a skill-specific productivity parameter. These linearity assumptions are not essential for the main quantitative results of the paper but simplify the exposition and computation of the model. We illustrate the implications of different elasticities of substitution across schooling groups in Section 5.

The technical parameters z_t and z_{it} are the only exogenous variables in the economy. Since our focus is on long-run trends, we assume constant growth rates:

$$
\begin{aligned}
z_{t+1} &= g z_t && \forall t \\
z_{i,t+1} &= g_i z_{it}, && \text{for } i = 1, 2, 3; && \forall t.
\end{aligned}
$$

Equation (1) implies that the following normalization is innocuous: $z_{1t} = 1$ for all t, thus $g_1 = 1$. Regarding the level of z_t, we set it to one at an arbitrary date. As it will transpire shortly, this normalization is innocuous too. The determination of the levels of z_{2t} and z_{3t} is discussed in Section 3.

We consider a market arrangement where there is a large number of competitive firms in both product and factor markets that have access to the production technology. Taking the

output good as the numeraire, the wage rate per unit of human capital is given by

$$w_t(s_i) = z_t z_i.$$

The youngest worker of type i at date t is of age $s_i + 1$ and thus, was "born" in period $t - s_i$, i.e. of age 1 at date $t - s_i$. The oldest worker is T-period old and was born in period $t - T + 1$. Thus,

$$H_{it} = \sum_{\tau=t-T+1}^{t-s_i} p_{i\tau} h(s_i, e_\tau(s_i)),$$

where $p_{i\tau}$ is the fraction of cohort τ that has attained the ith level of education, and $e_\tau(s_i)$ is the optimal schooling quality of this cohort. The discussions of $e_\tau(s_i)$ and $p_{i\tau}$ are postponed to Sections 2.3 and 2.4.

2.3 Households

Preferences are defined over consumption sequences and time spent in school. They are represented by the following utility function, for an agent of cohort τ:

$$\sum_{t=\tau}^{\tau+T-1} \beta^{t-\tau} \ln(c_{\tau,t}) - as,$$

where $\beta \in (0,1)$ is the subjective discount factor, $c_{\tau,t}$ is the period-t consumption of an agent of generation τ and, finally, $s \in \{s_1, s_2, s_3\}$ represents years of schooling. Note that a can be positive or negative, so that schooling provides either a utility benefit or a cost. The distribution of a is normal with mean μ and standard deviation σ:

$$A(a) = \Phi\left(\frac{a - \mu}{\sigma}\right),$$

where Φ is the cumulative distribution function of the standard normal distribution. The normality assumption on the utility cost of schooling is not essential for the results. In Section 5, we show that the shape of this distribution function is pinned down by the calibration so allowing for a more general distribution function with the same number of parameters delivers essentially the same quantitative results. The production function for human capital is

$$h(s, e) = s^\eta e^{1-\eta}, \qquad \eta \in (0,1).$$

The optimization problem of a cohort-τ individual with ability a, conditional on going to school for s periods, is

$$\tilde{V}_\tau(a, s) = \max_{\{c_{\tau,t}\}} \left\{ \sum_{t=\tau}^{\tau+T-1} \beta^{t-\tau} \ln(c_{\tau,t}) - as \right\},$$

subject to

$$\sum_{t=\tau}^{\tau+T-1} \left(\frac{1}{r}\right)^{t-\tau} c_{\tau,t} = h(s, e_\tau) W_\tau(s) - e_\tau,$$

$$W_\tau(s) = \sum_{t=\tau+s}^{\tau+T-1} w_t(s) \left(\frac{1}{r}\right)^{t-\tau},$$

where the maximization is with respect to sequences of consumption and the quality of education e_τ. The budget constraint equates the date-τ value of consumption to the date-τ value of labor earnings, $h(s, e_\tau) W_\tau(s)$, net of investment in quality, e_τ. The function $W_\tau(s)$ indicates the date-τ value of labor earnings per unit of human capital. Observe that the time cost of schooling is summarized in $W_\tau(s)$. Hence, the model features a time cost of schooling (foregone wages), a resource cost e_τ, and a utility cost a. Observe also that human capital is constant throughout the life cycle. In Section 4, we discuss the quantitative implications of extending the model to allow for human capital accumulation on the job. We also discuss the implications of allowing for the increase in life expectancy observed in the data.

An agent of generation τ chooses s once and for all to solve

$$\max_{s \in \{s_1, s_2, s_3\}} \tilde{V}_\tau(a, s). \tag{2}$$

This problem can be solved in three steps. First, given s, it simplifies to a utility maximization problem which can, in itself, be divided into two parts. Specifically, the optimal investment in the quality of education, that is e_τ, maximizes net lifetime earnings. Then, given net lifetime earnings, the agent optimally allocates consumption through time using the credit markets. Hence, conditional on s, the optimal investment in quality, for an agent of cohort τ is

$$e_\tau(s) = \arg\max_e \{h(s, e) W_\tau(s) - e\},$$

which yields

$$e_\tau(s) = s[W_\tau(s)(1 - \eta)]^{1/\eta}.$$

The optimal amount of human capital is

$$h(s, e_\tau(s)) = s[W_\tau(s)(1 - \eta)]^{(1-\eta)/\eta}. \tag{3}$$

For later reference, we define the period t labor income of an agent of cohort τ with education s_i as $L_{i,\tau,t} = h(s_i, e_\tau(s_i)) w_t(s_i)$ for $t \geq \tau + s_i$. The net lifetime income of an agent of cohort τ is $I_\tau(s) = h(s, e_\tau(s))W_\tau(s) - e_\tau(s)$ or

$$I_\tau(s) = \kappa s W_\tau(s)^{1/\eta}, \tag{4}$$

where $\kappa = (1 - \eta)^{(1-\eta)/\eta} - (1 - \eta)^{1/\eta}$. The optimal allocation of consumption through time, given $I_\tau(s)$, is dictated by the Euler equation, $c_{\tau,t+1} = \beta r c_{\tau,t}$, and the lifetime budget constraint. At this stage, it is convenient to define $V_\tau(s) \equiv \tilde{V}_\tau(a, s) + as$. In words, the function $V_\tau(s)$ is the lifetime utility derived from consumption only, for an agent of cohort τ with s periods of schooling. Note that $V_\tau(s)$ is not a function of a. The optimal schooling choice described in (2) can then be written as

$$\max_{s \in \{s_1, s_2, s_3\}} \{V_\tau(s) - as\}. \tag{5}$$

2.4 Equilibrium

An equilibrium is a sequence of prices $\{w_t(s_i)\}$ and an allocation of households across schooling levels such that, for all t, $w_t(s_i) = z_t z_{it}$ and households of any cohort τ solve problem (2) given prices.

In equilibrium each cohort is partitioned between the three levels of schooling. The determination of this partition is described in Figures 4 and 5. Figure 4 describes an individual's optimal schooling choice by comparing the value functions $V_\tau(s) - as$ across the three levels s_1, s_2 and s_3. Each pair of value functions has one intersection.[6] An individual of type a chooses the schooling level which delivers the highest value. Specifically, consider an individual choosing between s_i and s_j, with $i > j$ and $i, j \in \{1, 2, 3\}$. The individual chooses s_i over s_j whenever the individual's utility cost of schooling is low enough, that is whenever $a < a_{ij,\tau}$ where $a_{ij,\tau}$ is a threshold utility cost for which an individual with such utility cost

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[6]The implication that there exist one intersection between each pair of value functions is a result of the infinite support for a and that $s_3 > s_2 > s_1$. To see this, note that as long as $V_\tau(s)$ is finite there exists, for each generation, an individual with a low enough a, denoted by $\underline{a}_\tau$, such that

$$V_\tau(s_3) - \underline{a}_\tau s_3 > V_\tau(s_2) - \underline{a}_\tau s_2 > V_\tau(s_1) - \underline{a}_\tau s_1.$$

Then, the linearity and slopes of $V_\tau(s) - as$ imply that each pair of functions intersect once for some $a > \underline{a}_\tau$.

of schooling is indifferent between level i and j:[7]

$$V_\tau(s_i) - a_{ij,\tau}s_i = V_\tau(s_j) - a_{ij,\tau}s_j.$$

The educational attainment rates of cohort τ, denoted by $p_{i\tau}$, are then

$$p_{1\tau} = 1 - A(a_{21,\tau}), \tag{6}$$
$$p_{2\tau} = A(a_{21,\tau}) - A(a_{32,\tau}), \tag{7}$$
$$p_{3\tau} = A(a_{32,\tau}), \tag{8}$$

as illustrated in Figure 5.[8] It is possible to characterize the threshold utility costs as functions of the fundamentals. First, we can show that

$$a_{ij,\tau} = \frac{1 - \beta^T}{1 - \beta} \times \frac{1}{s_i - s_j} \times \ln\left(\frac{I_\tau(s_i)}{I_\tau(s_j)}\right).$$

Thus, the threshold utility costs are proportional to the semi-elasticity of lifetime income with respect to years of schooling. Given that z_t, z_{1t}, z_{2t} and z_{3t} grow at constant rates, we can write

$$W_\tau(s_i) = \sum_{t=\tau+s_i}^{\tau+T-1} w_t(s_i) \left(\frac{1}{r}\right)^{t-\tau} = z_\tau z_{i\tau} \frac{(gg_i/r)^{s_i} - (gg_i/r)^T}{1 - gg_i/r},$$

so that, using Equation (4), we obtain

$$\frac{I_\tau(s_i)}{I_\tau(s_j)} = \frac{s_i}{s_j} \left(\frac{z_{i\tau}}{z_{j\tau}} \times \frac{1 - gg_j/r}{1 - gg_i/r} \times \frac{(gg_i/r)^{s_i} - (gg_i/r)^T}{(gg_j/r)^{s_j} - (gg_j/r)^T}\right)^{1/\eta}. \tag{9}$$

Equation (9) shows that, in the model, changes in educational attainment are driven by skill-biased technical change. Remember that skill-biased technical change takes place only when the $z_{i\tau}$'s are growing at different rates, implying that $z_{i\tau}/z_{j\tau}$ is a function of time. Not surprisingly, holding everything else constant, an increase in $z_{i\tau}/z_{j\tau}$ raises schooling enrollment in level i and reduces it in level j.

We note that the level of TFP, z, is absent in the determination of the critical agents because the baseline model abstracts from any potential asymmetry between the changes in

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[7]Since individuals are indexed by their utility cost of schooling we also refer to the threshold a_{ij} as the critical agent.

[8]The infinite support for a ensures that there is always a non-empty set of individuals choosing the first level of schooling and another non-empty set of individuals choosing the third level. It is possible, however, that no individual finds it optimal to choose the second level. In such case, there is only one critical agent, $a_{31,\tau}$, defined by $V_\tau(s_3) - a_{31,\tau}s_3 = V_\tau(s_1) - a_{31,\tau}s_1$. We do not emphasize this case since it does not arise in our main quantitative work.

benefits and costs of schooling. A change in z affects the lifetime income of agents in the same proportion, regardless of their education, as well as the opportunity cost of education. This property of the model is common in the human capital literature, see for instance Bils and Klenow (2000). We show in Section 4 that allowing for TFP-level effects does not change our main quantitative conclusions. Note also that the growth rate of TFP, g, appears in Equation (9). So, while g affects the level of educational attainment – a higher growth rate of income increases the optimal amount of schooling – it does not affect the evolution of educational attainment over time in our baseline experiment since we keep this growth rate constant. Finally, life expectancy, T, also appears in the determination of the critical agents. Increases in T promote educational attainment. To understand this, suppose that there is no skill-biased technical progress. Then, an increase in T raises the working life of the more educated proportionately more than that of the less educated and, therefore, it also raises their relative lifetime income. When there is skill-biased technical change this effect is even stronger. We keep T constant in our baseline experiment but we explore its quantitative contribution to educational attainment in Section 4.

3   Quantitative Analysis

This section proceeds as follows. In Section 3.1 we discuss the calibration which consists of two stages. First, some parameters are assigned numerical values using a-priori information. Second, the remaining parameters are calibrated to match key statistics of the U.S. economy for the year 2000, as well as overall growth in GDP per worker and relative earnings across schooling groups during the period 1940 to 2000. Unlike the business cycle literature, where the evolution of productivity is calibrated independently to Solow residuals, we do not have independent measures of our main driving forces. These measures are derived in the second stage of the calibration. It is important to emphasize that the actual evolution of educational attainment between 1940 and 2000 is not used for calibration. Thus, the quantitative importance of the mechanisms built into the model can be assessed by their ability to generate trends in educational attainment as displayed in Figure 1. In Section 3.2, we use our measures of technical change to assess their quantitative contribution in explaining the rise in educational attainment in the U.S. economy. In Section 3.3 we propose a series of experiments to decompose the role of each component of technical change. Finally, in Section 3.4 we consider alternative assumptions about what happens to skill-biased technical progress after 2000.

3.1 Calibration

The first stage of our calibration strategy is to assign values to some parameters using a-priori information. We let a period represent one year and consider that agents are born at age 6. The length of model life is set to $T = 60$, the gross interest rate to $r = 1.05$, and the subjective discount factor to $\beta = 1/r$. The length of schooling, s_1, s_2, and s_3, are set to the average time spent in school at each educational category for the 25-29 year-old white males in the 2000 U.S. Census. This restriction dictates $s_1 = 9$, $s_2 = 13$ and $s_3 = 18$.

The list of remaining parameters is

$$\theta = (\mu, \sigma, \eta, g, g_2, g_3, z_{2,2000}, z_{3,2000})$$

which consists of the distribution parameters for the utility cost of schooling, the human capital technology, and growth rates and levels for productivity variables. We build a measure of the distance between statistics in the model and the corresponding statistics in the U.S. data. The procedure targets the following statistics: (i) the educational attainment of the 25-29 years old in the 2000 Census which are 13.4 percent less than high school and 58.8 percent high school;[9] (ii) the share of time in the total cost of education in 2000 of 90 percent – see for instance Bils and Klenow (2000); (iii) the time path of relative earnings from 1940 to 2000; and (iv) the growth rate of GDP per worker from 1940 to 2000 which was on average 2 percent. We then choose each element of θ simultaneously to minimize this function.

Even though parameter values are chosen simultaneously to match the data targets in (i) to (iv), each parameter has a first-order effect on some target. For instance, the levels of skill-biased technology, $z_{i,2000}$, and their growth rates, g_i are important in matching the time path of relative earnings across schooling groups. The growth of TFP g is important in matching growth in average labor productivity. The time share η is important for the share of time in human capital accumulation.[10] The utility cost of schooling parameters, μ and σ, are crucial in matching the distribution of educational attainment in 2000.

The calibration procedure can be described formally as follows. Given a value for θ we compute an equilibrium and define the following objects. First,

$$\hat{E}_{ij,t}(\theta) = \frac{L_{i,t-s_i,t}}{L_{j,t-s_j,t}}$$

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[9]The model counterpart to these statistics is educational attainment of the 1981 generation which is 20 years old in 2000 in the model and corresponds to age 25 in the U.S. data.

[10]It turns out that because the model abstracts from TFP-level effects, the shares of time and goods in the production of human capital are irrelevant for the quantitative properties of the baseline model. They do affect the earnings of a given schooling group across cohorts.

is the period-t earnings of an agent of generation $t - s_i$ and education level i, relative to that of an agent of generation $t - s_j$, with education level j. Observe that at date t both agents are just entering the labor force. This calculation is justified by the importance of age in earnings in the data. The empirical counterpart of $\hat{E}_{32,t}(\theta)$ is the relative earnings between college and high school, denoted by $E_{32,t}$. Similarly, $\hat{E}_{21,t}(\theta)$ is the model counterpart of $E_{21,t}$, the relative earnings of high school to less than high school. Second, we define

$$M(\theta) = \begin{bmatrix} p_{1,1981} - 0.134 \\ p_{2,1981} - 0.588 \\ x_{2000} - 0.90 \\ Y_{2000}/Y_{1940} - 1.02^{60} \end{bmatrix}$$

where x_t is the average share of time in the total cost of education.[11] Then, to assign a value to θ we solve the following minimization problem

$$\min_{\theta} \sum_{t \in \mathcal{T}} \left(\hat{E}_{32,t}(\theta) - E_{32,t} \right)^2 + \left(\hat{E}_{21,t}(\theta) - E_{21,t} \right)^2 + M(\theta)^{\top} M(\theta)$$

where $\mathcal{T} \equiv \{1940, 1950, \dots, 2000\}$.

The second column of Table 1 indicates the value of the calibrated parameters. The model is able to match exactly the calibration targets in terms of the moments summarized in $M(\theta)$. Also, the model implies a smooth path of relative earnings that captures the trend observed in the data as illustrated in Figure 6.[12]

3.2   Baseline Experiment

The main quantitative implications of the model are with respect to the time path of educational attainment. In particular, the model implies time paths for the distribution of educational attainment for the three categories considered: less than high-school, high-school, and college. Figure 7 reports these implications of the model. The model implies a substantial increase in educational attainment – an increase in average years of schooling of 48 percent

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[11]Formally, it is defined as

$$x_t = \frac{\sum_{i=1,2,3} p_{i,t} L_{i,t,t} s_i}{\sum_{i=1,2,3} p_{i,t} (L_{i,t-s_i,t} s_i + e_t(s_i))}.$$

[12]Our specification of skill bias has only two parameters per relative skill level, as a result, the best the calibration can do is to fit a trend line through the data points. As we will discuss below, skill bias produces a substantial effect on educational attainment so the exact parametrization matters for the quantitative results. In Section 3.3 we discuss the results in light of different assumptions regarding skill-biased technology.

between 1940 and 2000 compared to 27 percent in the data.[13] By construction of our calibration strategy, the model implies an average years of schooling of 13.9 as in the data for 2000. In 1940, the model implies an average years of schooling of 9.4, whereas in the data this average is 10.9 years. In terms of the distributions, the fraction of 25 to 29 year-old with college education increases in the model by 28 percentage points from 1940 to 2000, while in the data the increase is 20 percentage points. For high school, the model implies an increase from 10 to 60 percent between 1940 and 2000 whereas, in the data, the increase is from 30 to 60 percent. The model implies a roughly constant share of expenditures in education over GDP around 4 percent which is in the ball park of estimates in Haveman and Wolfe (1995).

We chose the year 2000 for most of our calibration targets. Given how different the educational attainments are in 1940, the question arises whether the results depend on this choice. We investigate this issue by calibrating the economy to data for 1940 instead. The calibrated parameters are presented in the last column of Table 1. Note that the parameters are reasonably close in each calibration, except for μ and σ, which should not be a surprise.[14] Given this alternative calibration, the quantitative results are fairly similar, for instance, the increase in average years of schooling from 1940 to 2000 is around 50 percent, close to the 48 percent increase in the baseline model calibrated to data in 2000. One interesting aspect of the results of the calibration to 1940 data is that, while the underlined quantitative force of technological progress on educational attainment is the same, the results presented in this way emphasize one aspect of the data that the baseline experiment is not able to capture – namely the slowdown in educational attainment starting in the mid 1970's (see Figures 1 and 8). We come back to this issue in Section 3.4 where we discuss alternative assumptions about skill-biased technical change after the year 2000. We show that these alternative assumptions can potentially rationalize the observed slowdown in educational attainment.

3.3   Decomposing the Forces

The motivation for our approach is to exploit the observed earnings heterogeneity in a parsimonious environment to isolate its contribution on the evolution of educational attainment. In light of this, we decompose the importance of the exogenous forces leading to labor productivity and earnings growth by running a sequence of counterfactual experiments. These

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[13]We compute average years of schooling of the 25 to 29 year-old population implied by the model as $\sum_i s_i p_i$ in each year. We do the same for the data, i.e., we use the attainment data together with the calibrated s_i's.

[14]Table 1 reports the level of $z_{2,1940}$ and $z_{3,1940}$ which are the calibrated level parameters in this exercise. The paths z_{2t} and z_{3t} are remarkably close, however, in the two exercises. For example, the implied value of $z_{2,2000}$ and $z_{3,2000}$ in the 1940 calibration are 1.37 and 1.78, respectively.

experiments are reported in Table 2.

The first experiment is designed to assess the importance of the high school bias. We set $g_2 = 1$ and adjust g_3 such that g_3/g_2 remains the same as in the baseline case. We maintain the rest of the parameters at their baseline values. Measured by average years of schooling, the change in educational attainment falls to 10 percent from 48 percent in the baseline. Lower educational attainment growth leads to substantially lower labor productivity growth (1.3 vs 2 percent in the baseline). The second experiment assesses the role of the college bias. We assume that $g_3 = g_2$ with g_2 at its baseline value. In this case the earnings of college relative to high school does not change over time. The departure in this experiment in terms of average educational attainment is much less than in the previous experiment, average years of schooling increase by 31 percent instead of 48 percent in the baseline. Also, the college bias does not contribute much to overall productivity growth. In the third experiment, we shut down skill bias completely by imposing $g_2 = g_1 = 1$. As discussed previously, the model without skill-biased technical change does not generate any change in educational attainment and relative earnings. As a consequence, labor productivity growth is slightly above the value of g. Given the results from these experiments, we conclude that, in terms of skill-biased technical change, the high-school bias is the most important force behind the changes in educational attainment. More precisely, shutting down the high-school bias implies the largest departure from the baseline at the aggregate level (average years of schooling and the growth rate of the economy).

We emphasize that the educational attainment implications of the model are sensitive to the calibration of skill-biased technical change. The baseline calibration captures the overall trend in relative earnings over the 1940 to 2000 period. However, this trend is calculated only over 7 Census years and there is substantial decade-to-decade variation in relative earnings. We illustrate the quantitative importance of the trends in relative earnings by conducting a fourth experiment were we reduce by half the growth rate of relative earnings between 1940 and 2000. We accomplish this by adjusting the growth rates g_2 and g_3 so that the growth in relative technical progress of the two groups is reduced by half relative to the baseline calibration. We leave all other parameters the same. In this experiment, average years of schooling between 1940 to 2000 increase by 24 percent (27 percent in the data), while average growth in GDP per worker is 1.84 percent (2 percent in the data).

3.4 Alternative Paths for Relative Earnings

The baseline experiment provides a parsimonious representation of the increase in relative returns across schooling groups and its impact on educational attainment. More specifically, the baseline experiment assumes a constant growth rate in skill-biased technology that continues into the future. However, relative earnings since the 1990s show considerable slowdown. Given that schooling decisions are forward looking we can ask whether a slowdown in skill-biased technology can potentially explain the observed slowdown in educational attainment. We make the extreme assumption that there is no skill bias after the year 2000, i.e., we set $g_2 = g_3 = 1$ from 2000 onwards, leaving all other aspects of the baseline experiment the same. We find that the implied time path for educational attainment features considerably slowdown relative to the baseline calibration, see Figure 9. Intuitively, the model without skill-biased technology and constant TFP growth implies a constant path for educational attainment. As a result, the educational decisions of the cohorts that dominate the measure of educational attainment in the last part of the time series are highly influenced by the constant profile of relative earnings starting in 2000. Under this calibration, average years of schooling increase by 39 percent vis à vis 48 percent in the baseline.

4 Extensions

In this section we consider three extensions of the model mechanisms that can potentially affect the importance of relative earnings on educational attainment. First, we study a simulation of the model that allows for life-expectancy to change according to data. Since there has been a substantial change in life expectancy for the relevant cohorts in the sample period we ask whether this can provide an important source of changes in educational attainment. Second, we incorporate on-the-job human capital accumulation into the model. Human capital accumulated on the job affects lifetime income and therefore can affect educational attainment. Finally, in the spirit of Ben-Porath (1967), Manuelli and Seshadri (2006) and Erosa, Koreshkova, and Restuccia (2007), we extend the model to allow for TFP-level changes to affect schooling decisions. In all these extensions, we find that the importance of changes in relative earnings in generating a substantial increase in educational attainment remains unaltered.

4.1   Life Expectancy

There has been a substantial increase in life-expectancy in the United States. For males, life expectancy at age 5 increased from around 50 years in 1850 to around 70 years in 2000. Because the return to schooling investment accrues with the working life, this increase can generate an incentive for higher amounts of schooling investment. However, human capital theory also indicates that the returns to human capital investment are higher early in the life cycle rather than later (see for instance Ben-Porath (1967)) and as a result, increases in life expectancy may command a low return given that they extend the latest part of the life cycle of individuals. Whereas the increase in life expectancy is substantial, this life cycle aspect of the increase in life expectancy may dampen the overall contribution of this factor in promoting human capital investment. In this section we ask whether the increase in life expectancy is quantitatively important in explaining the increase in educational attainment and whether it dampens the contribution of relative earnings in our baseline model.

We proceed by simulating the model using the changes in life expectancy as observed in the data.[15] We recalibrate the economy in 2000 to the same targets but taking into account the changes in life expectancy. The main changes in the calibration relative to the baseline involve parameters pertaining to the distribution of utility cost of schooling and the growth rates of technology. Overall, we find that the increase in life-expectancy does not change the implications of the model substantially, in fact, life-expectancy has only modest effects in educational attainment during this period. We make this assessment by comparing the implications on educational attainment of the model calibrated to the changes in life expectancy with the model keeping life expectancy constant at its 2000 level. The model with changes in life expectancy generates an increase of 50 percent in average years of schooling. Holding life expectancy constant reduces this increase to 48 percent as in the baseline model. Hence, the change in life expectancy during this period explains 4 percent of the increase in educational attainment (2 percentage points out of 50). We conclude that while changes in life expectancy are substantial during this period, their effect on educational attainment are not quantitatively important.

4.2   On-the-job Human Capital Accumulation

The baseline model abstracts from human capital accumulated on the job. The data suggest that there are considerable returns to experience. The age profile of earnings, for example,

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[15]Specifically, the life expectancy of the period-t generation is $T_t = g_T T_{t-1}$ given an initial condition T_{1850}. The pair (T_{1850}, g_T) is chosen as to minimize the distance between the U.S. data and $[T_t]$, in a least square sense. (The notation $[\cdot]$ denotes the nearest integer function.)

are increasing in the data while our baseline model implies that they are decreasing. Returns to experience may affect educational decisions. First, if they increase with education – as we will show it is the case in the data – then this provides an additional return to schooling, reinforcing the effects of skill-biased technical change. Second, substantial returns to experience implies that, other things equal, individuals would have an incentive to enter the labor market sooner. Because of these opposing effects, it is a quantitative question whether on-the-job human capital accumulation affects the evolution of educational attainment over time.

We extend the model to consider the following human capital accumulation equation:

$$h(s, e) = s^\eta e^{1-\eta} x^{\gamma(s)},$$

where $x = a - s$ measures years of experience and $\gamma(s)$ is the human capital elasticity of experience for a worker who has completed s years of schooling. Note that we allow this elasticity to differ across schooling groups. This feature is motivated by the age profile of earnings observed in the year 2000 and displayed in Figure 10. The ratios of weekly earnings between a 55- and a 25-year old are 1.6, 1.9, and 2.1 for less than high school, high school, and college.

In our first pass at assessing the importance of returns to experience, we use the information presented in Figure 10 to calibrate this version of the model. That is, in addition to the baseline targets, we choose the three $\gamma(s_i)$'s to match the age profile of earnings in 2000.[16] In terms of educational attainment, the calibrated model with on-the-job human capital accumulation reduces the incentives to remain in school created by skill-biased technical progress. The average number of years of schooling increases from 10.9 in 1940 to 13.9 in 2000 – an increase of 27 percent which compares to 27 percent in the U.S. data and 48 percent in the baseline model. The calibrated returns to experience in this extension of the model dampen the incentives for schooling investment.

We note, however, that there is strong evidence that the returns to experience have been falling for recent cohorts in the U.S. data – see Manovskii and Kambourov (2005). To try and capture the effect of this decrease in returns to experience, we compare the life-profile of earnings of a 25 year old in 1940 versus a 25 year old in 1970 – see Table 3. A 25-year-old in 1940 can expect weekly earnings to increase by a factor of at least 2.74 when reaching 55 years of age. In sharp contrast, a 25-year-old in 1970 should not expect earnings to

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[16]The calibrated parameters g, g_2, and g_3 are 1.011, 1.005, and 1.010. We find $\gamma(s_1) = 0.36$, $\gamma(s_2) = 0.39$ and $\gamma(s_3) = 0.28$ for the human capital elasticity of experience. The calibrated model with on-the-job human capital accumulation matches the age profile of earnings in 2000 by construction.

increase by a factor of more than 2.15 when reaching 55. This "flattening" of the age profile of earnings does not affect equally all educational groups. In fact, the increase in earnings throughout the life cycle is enhanced more by education for the 1970 cohort than for the 1940 cohort: A 25-year old in 1940 would see weekly earnings increase 12 percent faster choosing high school versus less than high school. In 1970, the same individual would see earnings increase 28 percent faster by choosing high school. The same result holds, qualitatively, for college versus high school. Using these numbers and assuming an annual interest rate of 5 percent, we can build a back-of-the-envelope ratio of lifetime income across educational groups and generations. Consider, for example, the earnings of a 25-year old in 1940 with less than high school and normalize this to one. At age 55, earnings are 2.74, implying a present value of 24.9. For a member of the same cohort but in the high school schooling group, the present value of earnings is 26.3. Thus, high school increases the present value of earnings by 6 percent $(26.3/24.9 - 1)$ for a member of this generation. For a member of the 1970 generation the same calculation indicates that high school increases the present value of earnings by 10 percent. Similarly, college increased lifetime income by 7 percent for the 1940 generation versus 16 percent for the 1970 generation.

We conclude that the flattening of the life profiles of earnings across generations is conducive to attracting recent generations into more schooling. We use the model to compute educational attainment for the 1940 and 1970 cohorts. Adjusting the $\gamma(s_i)$'s to allow for the flattening of the life profiles of earnings, we find that the implied increase in educational attainment is close to the baseline experiment that abstracts from returns to experience (48 percent). Hence, changes in relative earnings generate a substantial increase in educational attainment and this effect is robust to the incorporation of reasonable returns to experience in the data.

4.3   TFP-Level Effects

The baseline model abstracts from TFP-level effects. Since there is a literature that emphasizes TFP-level effects in explaining schooling differences across countries, we extend the model to allow for these effects and assess whether they matter for our main conclusion that changes in relative earnings represent a substantial force in explaining the increase in educational attainment in the United States from 1940 to 2000. We follow Ben-Porath (1967) in allowing for TFP-level effects by extending our production function for human capital to include stages in human capital accumulation, where the human capital from previous schooling levels enter as an input in the production of human capital of the next level. In

particular, we assume the following human capital technology:

$$h_i = (s_i h_{i-1})^\eta e_i^{1-\eta},$$

where $i \in \{1, 2, 3\}$ denotes the schooling stage and $h_0 = 1$. The lifetime net income of an agent of generation τ is then

$$I_\tau(s_i) = \max_{e_1, e_2, e_3 \geq 0} \left\{ h_i W_\tau(s_i) - e_1 - e_2 - e_3 \right\}.$$

In this formulation, the efficiency units of labor of an agent are used either for producing goods in the market or for producing next stage human capital in school. This differs from the previous formulation where efficiency units of labor where used only in producing goods. The agent decides how much to spend at each level of schooling e_i. An implication of this extension is that a unit of spending in high school quality increases the marginal productivity of spending in college. Thus, when the level of income rises because of TFP, a one percent increase in education quality affects income proportionately more at the highest level of education. Formally, we can show that $d \ln I(s_i)/d \ln z = \eta^{-i}$ while in the baseline model this elasticity is $1/\eta$ at each schooling level i.

We calibrate this version of the model exactly as described in Section 3.1. We find that the increase in average years of schooling in the model is 48 percent, just as in the baseline model that abstracts from TFP-level effects. We then use this calibrated version of the model to compute the evolution of educational attainment predicted when skill-biased technical change is set to zero, that is when $g_2 = g_3 = 1.0$. Thus, TFP alone drives the results of this experiment. We find that average years of schooling increase by 5 percent and conclude that 10 percent (5/48) of the rise in average years of schooling is due to the increase in the TFP level. The remaining 90 percent is due to skill-biased technical change in the model.

5   Discussion

In this section we first evaluate the robustness of our main quantitative results to relevant variations in functional-form specifications. Namely, we introduce imperfect substitution across schooling groups in the output technology and we consider alternative distributions for the marginal utility of schooling. We find that the importance of changes in relative earnings in explaining the increase in educational attainment is remarkably robust to these variations. We end with a discussion of the implied income elasticity of educational attainment in the

model and relate it to the existing literature.

5.1   Substitution across Schooling Groups

We emphasize that the technology for aggregate human capital allows perfect substitution between skill groups. This assumption is less problematic than it may first appear. The reason is that our results do not emphasize a particular quantitative elasticity of skill-biased technical change to educational attainment. Neither do they emphasize a tight measurement of skill-biased technical parameters. Clearly those applications would necessitate tight measurements for the elasticities in the technology for aggregate human capital as well as other sources of labor productivity growth. Instead our emphasis is on the role of skill-biased technical change – as measured by the change in relative earnings – on educational attainment without explicit decomposition of the quantitative source. For instance, an alternative substitution elasticity in aggregate human capital would require a different quantitative source of skill-biased technology to match the same relative earnings paths. The discipline imposed on the quantitative results of the paper hinge on the relative earnings paths.

The following exercise illustrates this point. Consider, a general constant-elasticity-of-substitution technology for aggregate human capital:

$$H_t = \left[(z_{1t} H_{1t})^\rho + (z_{2t} H_{2t})^\rho + (z_{3t} H_{3t})^\rho \right]^{1/\rho},$$

where $\rho < 1$. Output is $Y_t = z_t H_t$. This specification implies an elasticity of substitution of $1/(1 - \rho)$ between skill groups. For values of ρ strictly below one different skill groups are more complementary than in the baseline specification, and an increase in any given z_{it} affects the wage rate of all skill groups.

For simplicity, we consider a steady-state situation in levels, that is a situation where z_t and the z_{it}'s are constant through time.[17] An equilibrium is a set of prices, $w(s_i)$, and an allocation of individuals across schooling levels such that:

$$w(s_i) = z \left[(z_1 H_1)^\rho + (z_2 H_2)^\rho + (z_3 H_3)^\rho \right]^{1/\rho - 1} (z_i H_i)^{\rho - 1} z_i,$$

and

$$H_i = (T - s_i) h(s_i, e(s_i)),$$

for $i \in \{1, 2, 3\}$, and individuals solve problem (2) given prices. The first condition above equates the marginal product of human capital for skill group i to its wage rate. The second

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[17]Our model does not have a balanced growth path.

equation is the labor market clearing condition for skill group i.

The nature of the exercise is similar to that of Section 3.1. We set s_1, s_2, s_3, T, r and β to their values in Table 1, and we fix z_1 to one. Then we proceed in two steps. First, we calibrate the steady state of the model to match the U.S. economy in 2000. Specifically, we have two targets for educational attainment rates, two for relative earnings and one for the share of time in the total cost of education. We impose $z = 1$ and we pick five parameters to match these targets: $(\mu, \sigma, \eta, z_2, z_3)$. In a second step, we re-calibrate z, z_2 and z_3. We choose them to match three targets: the relative earnings in 1940 and the ratio of GDP per capita between 1940 and 2000. Hence, as in the baseline calibration, this exercise uses the evolution of relative earnings to measure skill-specific technical change. We then ask by how much educational attainment is changing. We repeat this exercise for different values of ρ. This procedure delivers the equivalent of the baseline experiment described earlier. We also reproduce experiments 1 and 2 of section 3.3 in order to isolate the contribution of high school and college bias.

Table 4 reports the results. For selected values for ρ, the table shows educational attainment in 1940 and relative earnings in 2000 and 1940, for the baseline exercise and experiments 1 and 2. First, we note that there are differences between the steady-state version of the model with $\rho = 1$ and the dynamic version presented earlier. The steady-state version of the model implies a lower increase in educational attainment because of the absence of exogenous growth in earnings throughout the lifetime of individuals. Second, by comparing across steady-state economies with different values for ρ, Table 4 shows that the elasticity of substitution does not affect the main conclusions. Once skill-biased technical parameters are calibrated to match the evolution of relative earnings, changes in educational attainment across different calibrations for ρ are almost identical. This is true for the baseline exercise and the counterfactuals. In addition, it is interesting to note that the calibrated parameters for the human capital technology and the distribution of utility cost of schooling are hardly changing across these calibrations. Thus, the main effect of ρ is to impose different values for the skill-biased technical parameters in levels and rates of change.

We recognize that these results only apply to a steady-state version of the model. However, we expect that the same quantitative effects will carry through in the dynamic version of the model with different elasticities of substitution across skill groups. Data limitations prevent us from carrying through these experiments. When $\rho < 1$, the dynamic version of the model requires much more data than presently available. The reason for this is that in the model with $\rho < 1$, the wage rate at a point in time depends on the educational attainment of all cohorts working. Thus, this will require data on relative earnings going as

far back as 1900 or before. And wages are necessary to solve for human capital and earnings in 1940. When $\rho = 1$, wages are only a function of technical parameters at each date. Assuming perfect substitution across skill groups in the human capital technology not only allows us to assess the role of technical change in educational attainment in a simple and tractable framework, but also gives us a reasonable characterization since the quantitative implications of the model turn out to be insensitive to alternative substitution elasticities after the model is calibrated to match the same relative earnings targets.

5.2   Distribution of Marginal Utility of Schooling

The model assumes a normal distribution to represent heterogeneity in preferences. Are the results robust to this choice? Intuitively, alternative distributional assumptions may deliver different implications for the evolution of educational attainment. In fact, changes in educational attainment depend on the distribution of the marginal cost of schooling time, as can be seen from Equations (6) to (8). To address this issue, we consider a more general distribution function: the Beta distribution. This distribution is defined on the unit interval and characterized by two parameters, μ and σ. Depending on the parameters, its density can be uniform, bell-shaped or u-shaped and it is not necessarily symmetric. Our question is whether the calibration described in Section 3.1 imposes enough discipline on the distribution of schooling utility so as to identify the elasticity of educational attainment to relative earnings.

We selected the Beta distribution because it has two parameters and, therefore, we can keep our calibration strategy while allowing the distribution of schooling utility to be potentially different from a normal. To make comparisons with the baseline case, where a can take any value on the real line, we write the utility function of an agent born at τ as

$$\sum_{t=\tau}^{\tau+T-1} \beta^{t-\tau} \ln\left(c_{\tau,t}\right) - \left(Ma - \frac{M}{2}\right)s,$$

where a is distributed according to a Beta distribution with parameters μ and σ, and M is a positive number. The role of M is to map the domain of a into the interval $[-M/2, M/2]$, therefore allowing an arbitrarily large range for the marginal utility of schooling time.

We calibrate the model and compute the path of educational attainment with a Beta distribution for a range of M values. We compare the results to the baseline by computing the sum of squared differences between the paths of educational attainment. That is, we

compute

$$\epsilon = \sum_{t=1940}^{2000} \sum_{i=1,2,3} (p_{it}^{\text{normal}} - p_{it}^{\text{beta}})^2.$$

We also compute the mean and standard deviation of the marginal utility of schooling. In the baseline case they are, as indicated in Table 1, $\mu = 2.16$ and $\sigma = 0.62$, respectively. When $M = 50$ we find $\epsilon = 7.13 \times 10^{-2}$ and the mean and standard deviation of the marginal utility of schooling are 2.10 and 0.63. When $M = 100$, we find $\epsilon = 1.95 \times 10^{-6}$. Finally, for $M = 500$ we find $\epsilon = 7.35 \times 10^{-8}$ and the mean and standard deviation of the marginal utility of schooling are essentially the same as in the baseline case.

We emphasize that, in these exercises, the calibration strategy is the same as the one described in Section 3.1 – only the 2000 educational attainment data are used to identify the distribution of schooling utility. Our results indicate that the calibrated parametrization of the Beta distribution is quite close to the Normal used in the baseline and, consequently, the paths of educational attainment are nearly identical. Hence, our results are robust to potential departures from a normal distribution for schooling utility. We conclude that the calibration of the distribution of schooling utility to educational attainment at a point in time imposes enough discipline to pin down the elasticity of educational attainment to relative earnings.

5.3   The Elasticity of Educational Attainment

The model delivers an elasticity of educational attainment to changes in relative earnings (technical progress and lifetime income). In the previous section we argued that the main discipline of that elasticity comes from the calibration to the distribution of educational attainment at a point in time. Next we would like to discuss the magnitude of the implied elasticity.

There is a large empirical literature assessing the impact of educational policy on schooling. Some studies focus on finding the response of college attainment to changes in subsidies (short-run elasticities) while other focus on factors that alter lifetime behavior (long-run elasticities). Examples of this literature include Dynarski (2002, 2003), van der Klaauw (2002), and Keane and Wolpin (1997). While there is no complete agreement on the exact magnitude of these elasticities, the evidence suggests that they are large and we use this evidence to provide a benchmark against which to assess the magnitude implied by our quantitative results. For instance, Keane and Wolpin (1997) estimate a life-cycle model of schooling and career choices. Their structural estimates imply that subsidizing college costs by about 50

percent increases college completion from 28.3 to 36.7 percent. To construct an elasticity, we assume that the subsidy represents between 0.5 to 2 percent of lifetime income. This implies an elasticity of college completion between 52 and 13. To summarize the elasticity of educational attainment across cohorts in our model, note that the relative lifetime income of a college educated agent increases approximately by a factor $(g_3/g_2)^{60} = 1.32$ between the 1921 and the 1981 generation, while their respective educational attainment increases from 2.5 to 27.8 percent.[18] This yields an elasticity in the model of 8.7.

Studies that focus on short-term elasticities estimate even larger elasticities than the one in Keane and Wolpin (1997). Dynarski (2003) studies an exogenous change in education policy – namely the elimination of the Social Security Student Benefit program in the United States in 1981 – that affected some students but not others. Dynarski found that $1000 ($ of 2000) in college subsidy generates an increase in college enrollment of 3.6 percentage points. This can be translated into an elasticity if we assume that the amount of subsidy is the equivalent of 0.2 percent of lifetime income, implying an elasticity of college enrollment of 61. The elasticity of college completion would be around 31.[19] Alternatively, we can try to represent the finding in Dynarski doing the same policy experiment in our model. To get an increase in college enrollment of 3.6 percentage points for the 1981 generation in the model, a subsidy to college that is close to 2 percent of lifetime income is needed. We think this is a much larger number than $1000 in college subsidies. We conclude that the large increase in educational attainment in the baseline model comes from strong changes in relative earnings and not from an implausibly large elasticity of educational attainment to changes in income.

5.4 Further Implications

Our theory emphasizes relative earnings through skill-biased technical change as an important source of movements in educational attainment over time. In Figure 2 we emphasized that the evolution of educational attainment was similar for men and women. For our model to be consistent with these trends, changes in relative earnings would have to be about the same magnitude for men and women. Using data from the U.S. Census we decompose relative earnings across schooling groups for men and women. We find that the trend behavior of relative earnings across schooling groups are remarkably similar between men and women – see Figure 11. This process would imply a similar evolution of educational attainment

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[18]We focus on the 1921–1981 generations because, in the model, we assume that agents are born at age 6. A 25-year old in 1940 was 6 years old in 1921. Similarly, a 25-year old in 2000 was 6 years old in 1981.

[19]Similar elasticities are found by other empirical studies with different experiments, see for instance Dynarski (2002) and van der Klaauw (2002). Perhaps the larger elasticity implied by these studies is related to credit constraints that affect college enrollment.

across genders in the model, which is consistent with the data. Whereas the data for relative earnings indicates similar skill-biased technical change for men and women – with comparable evolution of education across genders – there is also a substantial and declining gender wage gap during this period. Hence, it appears that the gender wage gap has not played a major role for schooling investments across genders.

6   Conclusion

We developed a model of schooling decisions to address the role of changes in relative earnings through technological progress on the rise of educational attainment in the United States between 1940 and 2000. The model features discrete schooling choices and individual heterogeneity so that people sort themselves into the different schooling groups. Technological progress takes two forms: neutral and skill biased. Skill-biased technical change increases the returns of schooling thereby creating an incentive for more people to attain higher levels of schooling. We find that this source of technological progress is quantitatively important in explaining the increase in educational attainment in the United States between 1940 and 2000. More specifically, we found that the high-school bias is quantitatively more important for the educational trends than the college bias. The substantial changes in life expectancy turns out to explain almost none of the change in educational attainment in our model.

We have focused on the long-run trend of educational attainment in the United States. Two issues would be worth exploring further. First, while the model with skill-biased technical change can generate the overall trend in educational attainment, the model would need a flattening of the skill-biased profile somewhere after the 90s or before in order to be consistent with the slowdown in educational attainment since the late 70s. Second, it would be interesting to assess the role of skill-biased technical change in other contexts such as across genders, races, and countries. In particular, it would be relevant to investigate changes in relative earnings in countries with different labor-market institutions. Institutions that compress wages may reduce the incentives for schooling investment and it would be interesting to see (holding other institutional aspects constant) whether this wage compression can explain the lower educational attainment in European and other countries compared to the United States. Our analysis has taken the direction of technical change as given. It would be interesting to study quantitatively human capital accumulation allowing for endogenous technical change in the spirit of Galor and Moav (2000). We leave all these relevant explorations for future research.

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A   Data

The main source of data is the U.S. Census (1 percent samples from IPUMS, 1940-2000). The income variable is INCWAGE, which reports the respondent's total pre-tax wage and salary income. This variable is available at each census date from 1940 to 2000, and is intended to capture all monetary compensations received for work as an employee. Earnings are divided by the number of weeks worked. This is computed from WKSWORK2, which reports the number of weeks worked, by intervals. (We use the mid-point of the interval). This variable is available at each Census from 1940 to 2000. A variable reporting the exact number of weeks worked exists at some, but not all, Census dates. The education variable is EDUCREC which indicates the highest grade or year of college completed. The categories for EDUCREC are: 1 for N/A or No schooling; 2 for Grades 1 through 4; 3 for Grades 5 through 8; 4 for Grade 9; 5 for Grade 10; 6 for Grade 11; 7 for Grade 12; 8 for 1, 2, or 3 years of college; and 8 for 4 years of college or more. For each educational level, we focus on a different age group, in order to compare the earnings of agents with similar levels of experience. Furthermore, since our baseline model is about the returns to schooling and not experience, we focus on the youngest age groups. More specifically, the Less-than-high-school group is represented by 15-to-21-year-old reporting EDUCREC between 1 and 6, the High-school-or-more group is represented by 18-to-24-year-old reporting 7 or 8. Finally, the College group corresponds to by 21-to-27-year-old reporting 9. We restrict our analysis to white (RACED) males (SEX) working (EMPSTAT) for a wage or salary in the private or public sector (CLASSWKR). For each group, the bottom and top one percent of the distribution is ignored.

The source of data for Figures 1 and 2 is the Current Population Survey. The "Less-than-high-school" category corresponds to the percentage of the 25-29 year-old population who has completed less than four years of high school. The "High-school-or-some-college" category is the percentage of the 25-29 year-old population who has completed four years of high school or more, but less than four years of college. Finally, the "College" category corresponds to those who have completed four years of college or more. There are no differences between the educational attainment numbers displayed in Figures 1 and 2 and the numbers from the U.S. Census.

To calibrate s_1, s_2 and s_3, we use the variable EDUCREC from the U.S. Census, as described above. We compute the average years of schooling at each of the three levels in 2000.

Table 1: Calibrated Parameters

Interpretation	Parameters 2000 Calibration	Parameters 1940 Calibration
Length of schooling	$s_1 = 9$, $s_2 = 13$, $s_3 = 18$	
Length of life	$T = 60$	
Subjective discount factor	$\beta = 0.95$	
Interest rate	$r = 1/\beta = 1.05$	
Human capital technology	$\eta = 0.88$	$\eta = 0.89$
Distribution of abilities	$\mu = 2.16$, $\sigma = 0.62$	$\mu = 1.45$, $\sigma = 0.69$
Growth rates		
Neutral technology	$g\ = 1.0104$	$g\ = 1.0070$
HS biased technology	$g_2 = 1.0045$	$g_2 = 1.0046$
College biased technology	$g_3 = 1.0092$	$g_3 = 1.0094$
Level conditions		
HS biased technology	$z_{2,2000} = 1.37$	$z_{2,1940} = 1.05$
College biased technology	$z_{3,2000} = 1.78$	$z_{3,1940} = 1.02$

Table 2: Decomposing the Role of Skill-Biased Technology and TFP

	Baseline	Exp. 1	Exp. 2	Exp. 3	Exp. 4
Years of Schooling					
2000	13.85	13.16	13.14	12.55	13.16
1940	9.38	12.01	10.03	12.55	10.61
Ratio	1.48	1.10	1.31	1.00	1.24
Ratio of Relative Earnings 2000/1940					
College/HS (*)	1.38	1.38	1.00	1.00	1.17
HS/Less HS (**)	1.36	1.00	1.36	1.00	1.16
Average Growth (%) GDP per Worker	2.00	1.26	1.96	1.18	1.84

Note – Exp. 1: No High-School bias i.e., $g_2 = 1.0$ and g_3 is adjusted such that g_3/g_2 remains as in the baseline case. Exp. 2: No College bias i.e., $g_3 = g_2 = 1.0045$. Exp. 3: No technical bias e.g., $g_2 = g_3 = 1.0$. Exp. 4: Half the High-School bias i.e., the growth rate of z_2 is divided by two and g_3 adjusted. (*) the ratio is $\hat{E}_{32,2000}(\theta)/\hat{E}_{32,1940}(\theta)$; (**) the ratio is $\hat{E}_{21,2000}(\theta)/\hat{E}_{21,1940}(\theta)$.

Table 3: Ratio of Earnings Age 55 to Age 25

	Less than high school	High school	College
25 in 1940	2.74	3.08	3.53
		$= 2.74 \times 1.12$	$= 3.08 \times 1.14$
	$\rightarrow$	$I_2/I_1 = 1.06$	$I_3/I_2 = 1.07$
25 in 1970	1.18	1.51	2.15
		$= 1.18 \times 1.28$	$= 1.51 \times 1.43$
	$\rightarrow$	$I_2/I_1 = 1.10$	$I_3/I_2 = 1.16$

Note – The figures are the ratio of real weekly earnings of a person at age 55 versus age 25, by educational groups and generations. I_i is the present value of earnings from age 25 to 55, by educational groups and generations, when earnings are normalized to one at 25 and the interest rate is 5 percent per year. See the appendix for the source of data and definitions.

Table 4: Sensitivity Analysis – Elasticity of Substitution across Education Groups (ρ)

	Exercise	$p_{2,1940}$	$p_{3,1940}$	$E_{21,2000}$ / $E_{21,1940}$	$E_{32,2000}$ / $E_{32,1940}$	μ_a / σ_a / η
$\rho = 1.0$ Dynamic	Baseline	0.0863	0.0042	2.0	1.8	2.165
				1.5	1.3	0.624
	Exp. 1	0.7472	0.0028	2.0	1.8	0.877
				2.0	1.3	
	Exp. 2	0.0000	0.1141	2.0	1.8	
				1.5	1.8	
$\rho = 1.0$ Steady State	Baseline	0.1459	0.0058	2.0	1.8	1.635
				1.5	1.3	0.669
	Exp. 1	0.8602	0.0058	2.0	1.8	0.851
				2.0	1.3	
	Exp. 2	0.0000	0.2164	2.0	1.8	
				1.5	1.8	
$\rho = 0.6$ Steady State	Baseline	0.1459	0.0058	2.0	1.8	1.635
				1.5	1.3	0.669
	Exp. 1	0.8602	0.0058	2.0	1.8	0.851
				2.0	1.3	
	Exp. 2	0.0000	0.2164	2.0	1.8	
				1.5	1.8	
$\rho = 0.4$ Steady State	Baseline	0.1459	0.0058	2.0	1.8	1.635
				1.5	1.3	0.669
	Exp. 1	0.8602	0.0058	2.0	1.8	0.851
				2.0	1.3	
	Exp. 2	0.0000	0.2164	2.0	1.8	
				1.5	1.8	

Figure 1: The Evolution of Educational Attainment for White Males, 25-29
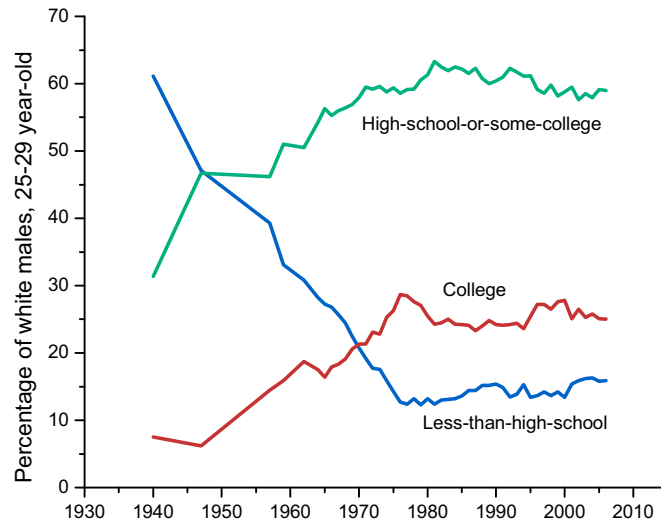
Note – See the appendix for the source of data and definitions.

Figure 2: The Evolution of Educational Attainment
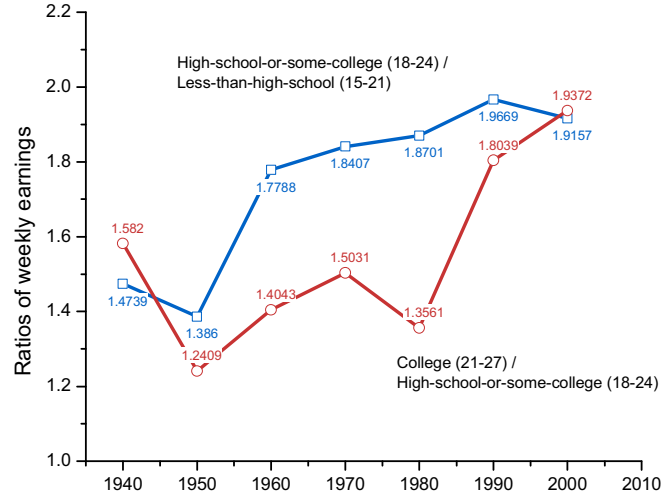
- White -   - Black -
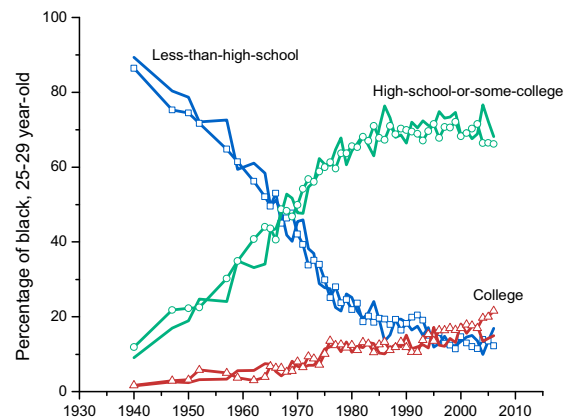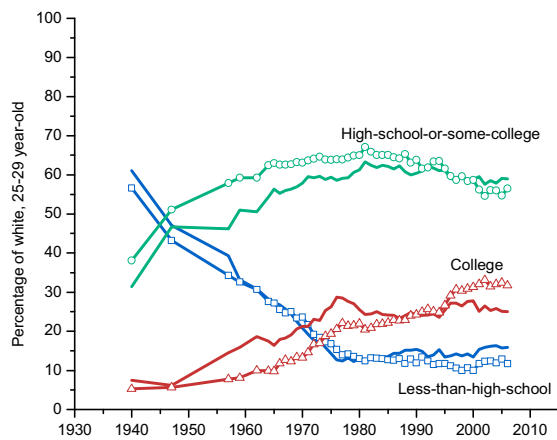
Note – See the appendix for the source of data and definitions. Women are represented with markers and men with solid lines.

Figure 3: Ratio of Weekly Earnings for Educational Groups – White Males

High-school-or-some-college (18-24) /
Less-than-high-school (15-21)

College (21-27) /
High-school-or-some-college (18-24)

Note – See the appendix for the source of data and definitions.

Figure 4: Individual Decision Problem

$V(s_1) - as_1$

$V(s_2) - as_2$

$V(s_3) - as_3$

$\underline{a}$

a_{32}

a_{21}

a
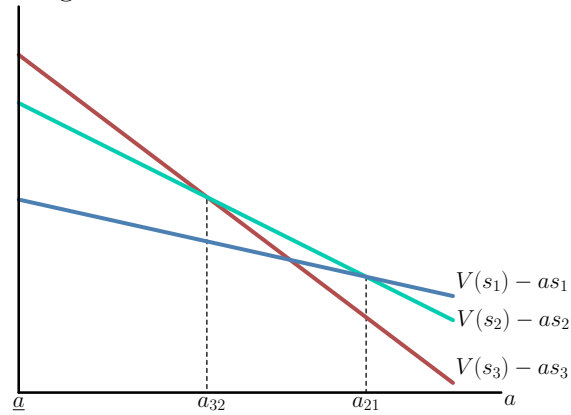
Figure 5: The Distribution of Schooling Attainment
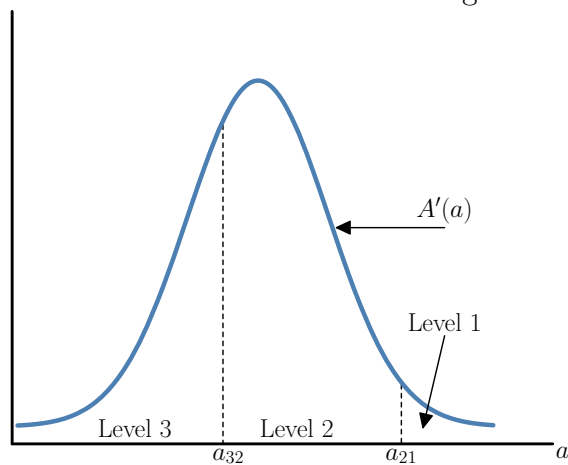
Figure 6: Relative Weekly Earnings – Model vs. Data
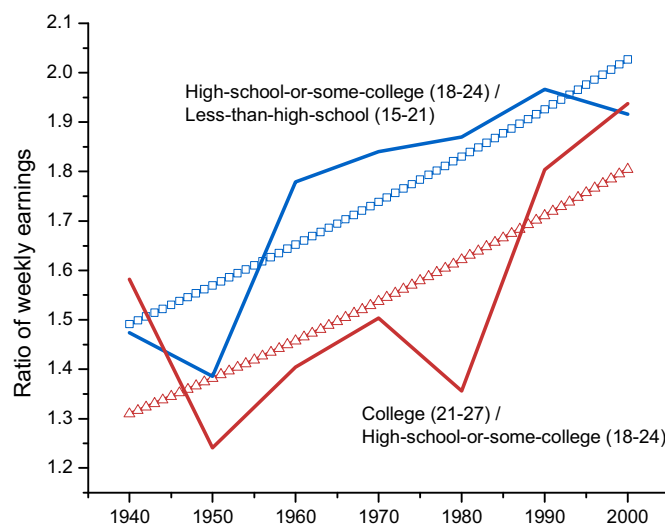
Note – The model data are represented with markers. The U.S. data are represented by solid lines.

Figure 7: Educational Attainment – Model vs. Data
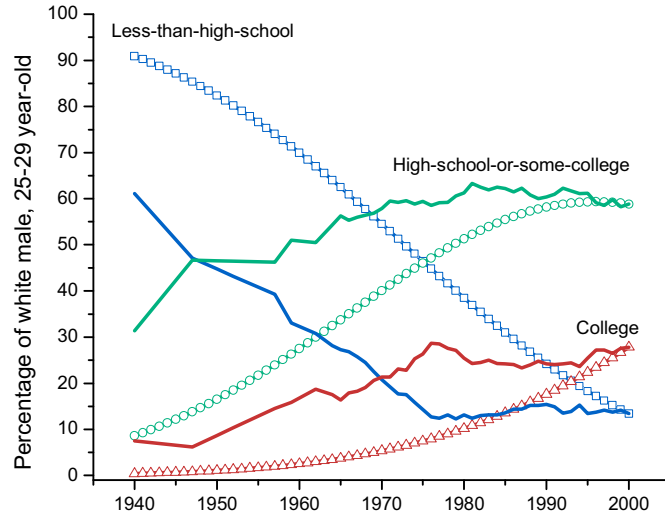
Note – The model data are represented with markers. The U.S. data are represented by solid lines.

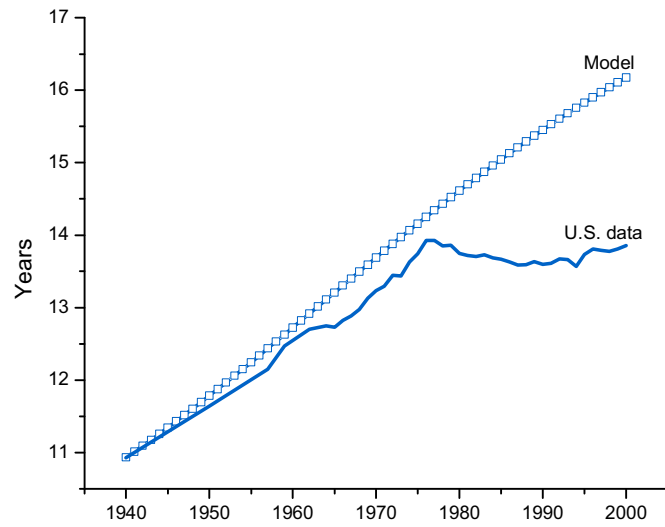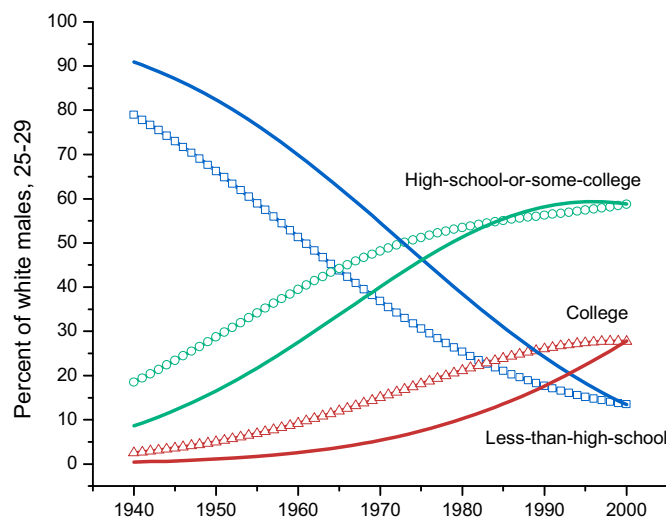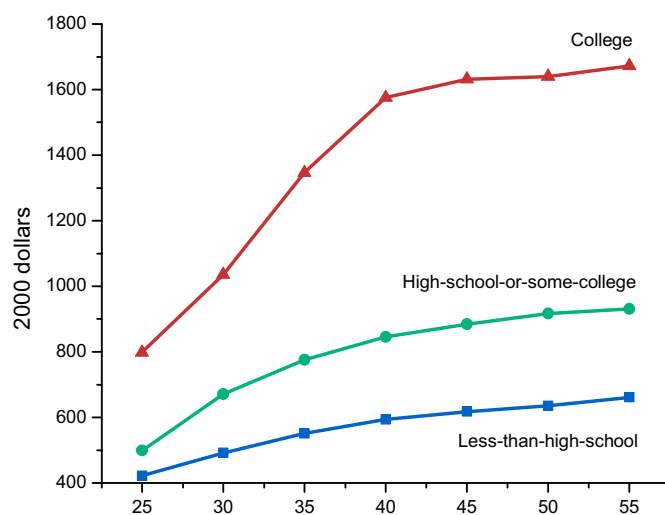Figure 8: Average Years of Schooling – Model Calibrated 1940 vs. Data

Figure 9: Educational Attainment – Model with Constant Relative Earnings after 2000 vs. Baseline


Note – The baseline calibration is represented with solid lines. The calibration with constant relative earnings after 2000 is represented with markers.

Figure 10: Age Profile of Earnings in 2000

Note – See the appendix for the source of data and definitions. For each educational group the data point at age a is the average weekly earnings of the $(a-5) - (a+5)$ age group.

Figure 11: Ratio of Weekly Earnings for Educational Groups – White Women
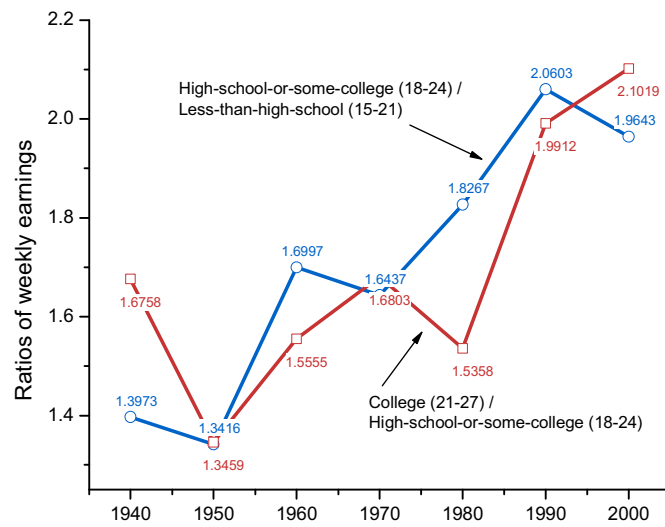
Note – The source of data is the U.S. Census. We use the exact same approach as the one described in Appendix A to build the series of relative earnings.